Estimation and quantification of vigilance using ERPs and eye blink rate with a fuzzy model-based approach

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Fuzzy Model-Based Approach to Vigilance Estimation using ERPs and Eye Blink Rate

Abstract. Vigilance or sustained attention is defined as the ability to maintain concentrated attention over prolonged time periods. Many methods for vigilance detection, based on biological and behavioural characteristics, have been proposed in the literature. In general, the existing approaches do not provide any solution to measure vigilance level quantitatively and adopt costly equipment. This paper utilizes a portable EEG device and presents a new method for estimation of vigilance level of an individual by utilizing ERPs (P300 and N100) of EEG signals and eye blink rate. Here, we propose a fuzzy rule-based system using amplitude and time variations of ERPs (N100 and P300) and blink variability to establish the correlation among N100, P300, eye blink and the vigilance activity. Besides, with the help of our proposed fuzzy model we efficiently calculate and quantify the vigilance level, and thereby obtain a numerical value of vigilance instead of its mere presence or absence. To validate the results obtained from our fuzzy model, we performed subjective analysis (to assess the mood and stress level of participants), reaction time analysis and compared the vigilance values with target detection accuracy. The obtained results prove the efficacy of our proposal.

1. Introduction

Vigilance is mainly described as a quality or state of alertness or watchfulness. It can also be thought of as the process of paying close and continuous attention to critical or rare events over prolonged intervals of time [1, 2, 3]. Vigilance is a concept closely related to attention; in fact, the word *attention* is often used while defining vigilance. In the literature, several slightly varying definitions for the term *attention* have been coined by the researchers working in different domains. Such definitions share a common central theme, that is, attention involves the concentration of thinking (cognitive processes) on a single object or thought to the exclusion of other stimuli or thoughts. Hence, many authors use the terms sustained attention and vigilance interchangeably. Vigilance or sustained attention is an important aspect especially in industries such as aviation, nuclear power and transportation wherein operators continuously perform monotonous and attention demanding tasks for long durations. However, it has been found that human alertness and vigilance drops over a course of time due to monotonicity of the job, high workload, time pressure, drowsiness, prolonged working hours, sleep deprivation, high working stress and distraction [4, 5]. Besides, it is also clear that different people have different tendencies to respond to vigilance tasks, hence, it is important to assign individuals selectively to tasks with high vigilance requirements [3]. Therefore, an effective system is needed that can continuously monitor the vigilance level of an operator and assess their ability in decision making, thereby play a dominant role in avoiding catastrophic situations arising due to deficit in vigilance.

In general, biological and behavioral attributes such as eye-closure, facial expressions, head position, heart beats, brain activity and reaction time have been used in the literature to develop ways and devices for vigilance detection. Corresponding to this, the authors in [6] used eyelid related features from Electro-oculogram (EOG) signals to develop a fuzzy expert system that can predict hypo-vigilance and help in providing early warning signals. A similar hypo-vigilance detection work has been reported in [7], which is based on facial image processing and where percentage of eye closure (PERCLOS), eye closure rate and eyelid distance changes have been used to detect hypo-vigilance among individuals. Monitoring the same parameters as in [7] along with blink frequency, nodding frequency, face position and fixed gaze, authors in [8] detected vigilance in drivers with the help of a hardware system and its software implementation, by acquiring drivers' images in real-time using an active IR illuminator. They also utilized a fuzzy classifier to infer the level of inattentiveness of the drivers. Other worth mentioning works [9, 10] utilized pupillometry, wherein authors measured eye features such as pupil diameter, pupil eccentricity and pupil velocity for vigilance detection. In [11], Körber *et al.* used the response time variations of the users and Dundee Stress State Questionnaire in addition to eye related features to study the variability of vigilance in individuals. Despite the fact that blink-related features appear to be a reasonable contender for hypo-vigilance detection, literature [6] demonstrates that these features are not exact and sufficiently dependable, since, they exhibit strong interpersonal (between persons) and intra-personal (same person different times) variability. Apart from the eye related features, Transcranial Doppler (TCD) sonography has been explored by the authors in [12] for both "go" and "no-go" response-based vigilance tasks. However, as TCD sonograph is not a portable device it can be quite uncomfortable if worn for longer time periods. Moreover, the TCD device is suitable mainly for people with thin skull structure [13]. Authors in [14], utilized electromyography and galvanic skin response (GSR) as features for detecting fatigue symptoms in drivers. However, GSR is very much affected by external factors (such as temperature and humidity) and internal factors (such as medications). In [15], Lee *et al.* estimated drivers' vigilance state by measuring the ECG from their palm, while they were driving the vehicle. On the same line, authors in [16] explored the impact of drowsiness on ECG and pulse signals. Vigilance estimation has also been done using a non-invasive and inexpensive system utilizing the photoplethysmography (PPG) signals [17]. The authors in [18] studied the impact of varying functional near infrared spectroscopy (fNIRS) signals on the performance of the task requiring sustained attention. Further, fNIRS has also been utilized to distinguish between high and low levels of task engagement during the execution of a selective attention task [19]. In [20], Tana *et al.* used functional magnetic resonance imaging (fMRI) to study the localization, magnitude, and volume extent of activation in brain regions that are involved in blood oxygen level-dependent (BOLD) response during the Conners Continuous Performance Test (CPT). Although these methods are very promising, fMRI involves huge equipment cost because of which fMRI can only be found at clinical centres for research purpose.

To better understand the dynamics of human brain and to accurately estimate vigilance, an alternate approach involving the use of an integrated hierarchical Gaussian mixture model (hGMM) and taking into account the EEG signals has been utilized in [21], wherein vigilance is determined using hGMM classifier with the help of features such as, power spectral density and error score. Nevertheless, the approach requires further study for generalization. In [22], authors proposed a hidden Markov model based hypo-vigilance detection, for Unmanned Combat Aerial Vehicle (UCAV) operators, in which EEG signals were captured while the participants were performing the tasks of varying difficulty level. The authors in [23] proposed a method to distinguish between two vigilant states (that is, sleep and awake) using spatio-temporal features of the EEG signals. They used the common spatial patterns to select vigilance related features from the recorded signals. Sauvet *et al.* [24] used the spectral power of each frequency band of EEG signals and their ratios as features to detect vigilance. Besides, they also used Karolinska Sleepiness Scale (KSS) for the subjective assessment of vigilance. Correlation between wavelet coefficients of the EEG signal bands and vigilance state of a person has been established in [25]. Further, authors in [25] used a sparse representation of these signals to classify the vigilance states. In [26], Zhang *et al.* presented a vehicle safety model for detecting drivers' drowsiness by making use of EEG and sparse representation where the authors first evaluated the Fast Fourier Transform (FFT) of EEG signals to calculate the power spectral density (PSD). Next, they combined sparse representation classification with k-singular value decomposition (KSVD) in PSD to estimate the vigilance level. A novel fatigue detection system, for high speed train safety, by assessing driver's vigilance through a wearable EEG is presented in [27]. In [28], authors presented a new application of adaptive neuro fuzzy system model for estimation of vigilance by using EEG signals recorded during transition from wakefulness to sleep.

Further, many researchers have used more than one biological traits for vigilance tasks. Zheng *et al.* [29] estimated vigilance by exploring the effects of EEG from different brain areas in combination with EOGs of forehead. In [30], authors investigated vigilance during detection, checking and response implementation tasks by subjective stress and workload estimation and assessment of EEG, ECG and hemodynamic responses in the context of a simulated operational scenario of a nuclear power plant. In [31], the authors estimated vigilance level by using both EEG and EMG signals to increase the estimation accuracy. Further, they measured the changes in EEG and EMG during transition from wakefulness to sleep using an artificial neural network. Sun *et al.* in [32] developed a system that can measure physiological signals such as EEG and ECG in real time for health monitoring and drowsiness detection. In [33], the authors simultaneously acquired fMRI and electroencephalographic measures of resting-state activity to assess the relation between the fMRI global signal and EEG measures of vigilance in humans. In [34], Czisch *et al.* used EEG and fMRI in liaison to study the effect of prolonged sleep deprivation on vigilance level. In [35], a system that combines information from multimodal data is presented to determine the state of alertness of an individual. Helton *et al*. [36] examined the impact of task interruptions on vigilance. Smit *et al*. show that vigilance decreases due to hard mental work requiring many resources [37].

The above discussed methods, developed by considering physiological signals exhibit a high degree of precision and have shown great deal of potential for vigilance detection. Out of many such methods, *non-invasive EEG-based methods* have become extremely popular amongst researchers for indicating vigilance, as brain signals can be studied in a relatively simple and inexpensive way with the help of EEG devices. Besides, the recent development of the portable, light weight, cost effective, hassle free, non-invasive EEG devices have made the accessibility of the brain signals very convenient [38].

EEG devices can capture four categories of statistical brain signals namely event-related desynchronization/synchronization (ERD/ERS) [39, 40, 41], steady state visual evoke potentials (SSVEP) [42], event related potentials (ERPs), and slow cortical potentials (SCPs). Amongst the above-mentioned brain signals, ERPs are especially very popular for attention/vigilance detection [43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53]. The motivation behind using ERPs for vigilance detection is: 1) rare or critical events evoke early and late ERP components that is, N100 and P300, respectively, and 2) ERPs have high temporal resolution that allows for the measurement of brain activity within milliseconds without any propagation delay. This allows to observe a series of cognitive operations taking place inside brain from an instant before the occurrence of a sensory information to an instant after the behavioural response. Besides, in a number of cases, the timing information provided by ERPs is very critical in resolving major theoretical issues in cognitive tasks. Further, the correlation between evoking of ERPs and stimulus discrimination task is already present in the literature [54, 55, 56]. Moreover, different combinations of ERPs and other features, namely N100-P200-P300, P50-N100-P200, P300-LPC (Late Positive Complex), N2-ERN (Error-related Negativity), P100-N100 have been used in [48, 49, 51, 53, 57, 58] for the purpose of performance monitoring, involuntary visuospatial attention study, multiple goal and trait inference study, studying the effect of faces expressing pain and personality judgement, etc.

It is already known that vigilance detection task involves monitoring of crucial information over prolonged time periods and these crucial information are usually infrequent and analogous to the task of stimulus discrimination. Therefore, by taking the advantage of this similarity between crucial information monitoring and stimulus discrimination, we propose to detect vigilance using ERP signals (P300 and N100). Besides, we utilize the high interdependence of blink rate (a non-ERP feature) with attention capabilities [59] in combination with N100 and P300 ERPs to establish correlation with alertness present in an individual. The motivation behind using blink rate in our study is that a high blink rate indicates low vigilance level of an individual and as, the amplitude of blink is significantly higher comparison to the rhythmic brain activity, this helps in the easy identification of eye blinks.

Although, the EEG signals are very effective in vigilance state discrimination - as they can directly read from the brain, yet, sometimes due to gradual change of states the demarcation is indistinguishable. This is a challenging task, as it makes it difficult to draw a sharp dividing lines between different states. Aiming to address the limitations of the current hypo-vigilance detection and accident warning systems, we propose a fuzzy rule-based system which can satisfactorily discriminate between various states of human alertness using ERPs (P300 and N100) and eye blink rate as features. With this aim, the objectives of our work are:

(i) To establish the correlation between ERPs (that is, N100 and P300) and the vigilance activity.

(ii) To establish a numerical relationship between N100 ERP, P300 ERP and eye blink (which is not so effective, if taken independently), such that these signals can be used in combination to obtain improved accuracy in vigilance detection.

(iii) To numerically measure the vigilance level of an individual, instead of its mere presence or absence.

(iv) To develop a fuzzy rule-base for efficiently calculating and quantifying the vigilance level.

To fulfil the above objectives, we have designed the experiments to evoke N100 and P300 ERP potentials for the critical stimulus. The N100 and P300 ERPs can easily be detected and analyzed from the brain signals; besides, for increasing the accuracy of the estimation we have also used eye blink activity in combination with both ERPs. Finally, to estimate the vigilance and quantify it numerically we have proposed a fuzzy rule-based system using amplitude and time variations of ERPs (N100 and P300) and blink variability.

The rest of the paper is organized as follows: Section 2 provides preparatory study about the ERP signals and the eye blink rate. Details about the proposed work has been explained in Section 3, which also explains the EEG data acquisition method (along with the experimental procedure) and EEG signal pre-processing and feature extraction methods. Section 4 presents the results and discussions. Finally, Section 5 concludes the paper.

2. Preliminaries

A brief account of N100, P300 and blink rate is given in the following:

2.1. N100 ERP for vigilance

The N100 ERP is mainly of two types that is, auditory and visual. In this work, we have used visual stimuli for eliciting N100, thereby detecting vigilance. Hence, the generated N100 falls into visual type. Usually, visual N100 is a negative deflection in EEG signals, elicited between 100 to 200 milliseconds after the onset of stimulus (refer to Figure 1). It is also known as as N1-P2 complex [60]. The amplitude of visual N100 is higher for a significant stimulus (N1-effect) in comparison to an insignificant stimulus

[61, 62, 63]. This helps in easy discrimination between vigilant and non-vigilant states of an individual. It is important to note here that significant stimulus represents the stimulus at which target appears while an insignificant stimulus represents all other non-target events.

2.2. P300 ERP for vigilance

P300 ERP was discovered by Sutton *et al.*, in 1965 [64]. It is evoked by both- a visual or auditory target stimulus in simultaneous presence of a target and non-target stimuli during the process of decision making (see Figure 1) [65, 66]. It is an endogenous potential, which can be seen as a positive deflection in the voltage with an average latency of roughly 250 to 600 ms (maximum up to 900 ms) depending upon the task [67], [68]. For example, the improbable event could be an infrequent target letter in a stream of letters to which a subject has to respond with a button press or mental counting of the target stimuli. The amplitude of P300 is larger when the stimulus is less probable and is usually in the range of 2-20 μV. Its occurrence is linked to a person's reaction to a stimulus. More specifically, the P300 reflects processes involved in stimulus evaluation or categorization.

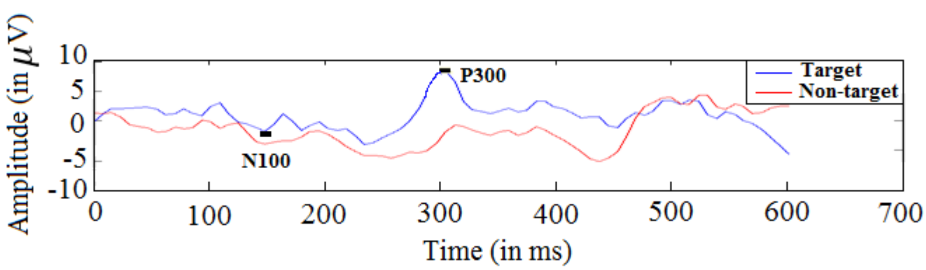


Figure 1: N100 and P300 components of ERP

2.3. Blink rate during vigilance

Eye-blinks, which are generally considered as an artifact in an EEG signal are commonly observable human behavior that usually occur in every four seconds or about 15 times in a minute [69]. It is easy to identify eye blinks in the EEG signals due to their higher amplitude (>40 μV) in comparison to the other brain rhythms (cf. Figure 2). Besides, it has been noticed by the researchers that blink rates vary quite a lot depending on emotional and mental states. Usually, stress and anxiety tend to increase a person's blink rate. However, intense concentration tends to reduce the blink rate, and in critical situations blinking rate can even go way down, presumably to help look around quickly without missing any event [70]. These findings suggest that thinking affects blinking and the spontaneous blink rate can serve as an indicator of the attentional demands of a cognitive task, since, the more attention a task requires the less often people blink.

This notion has recently received ample attention from an fMRI study in [71]. Figure 3 shows EEG signal displaying eye blink rate recorded during a vigilance activity.

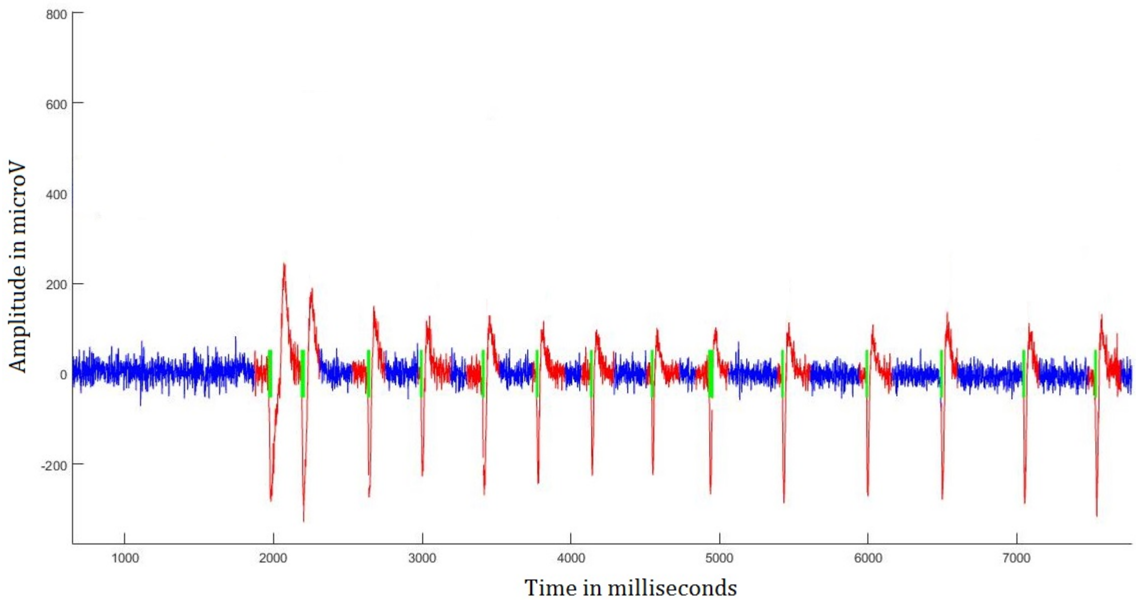


Figure 2: High amplitude peaks displaying eye blinks in EEG signal

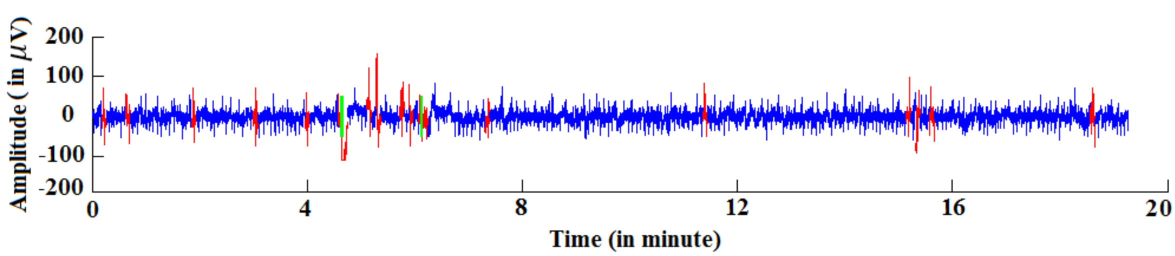


Figure 3: Eye blink during a vigilance activity

Recent studies [70, 72] validate that eye-blinks are directly associated with the attention mechanism. The authors also experimentally demonstrated that individuals with higher blink rates are inefficient in performing visual tasks and are more likely to commit errors. This proves the suitability of eye blink feature for vigilance detection [70].

3. Methods and Materials

3.1. Subjects

Ten healthy participants (male: 8, female: 2) comprising of research scholars and post-graduate students available on campus at IIT Kharagpur were randomly selected for this study. The participants had no history of mental ailment and their age ranged between

24-32 years. Each participant had normal or corrected-to-normal vision and were right handed. Besides, the participants were not sleep deprived; they had no deviations from their usual circadian cycle, and they took no medicine or alcohol. They were asked to refrain from having tea or coffee three hours before the experiment. Informed consent from all participants was taken before conducting the experiment. Appropriate certificate of approval was also obtained from the Institutional Ethical Committee at IIT Kharagpur.

3.2. Data Acquisition

Recording of the EEG data is done using the Emotiv Epoc+ device with 14 electrodes (following the 10-20 international system), at a sampling rate of 128 Hz. The 14 channels present in the device are: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4, with 2 references at P3/P4 locations. The bandwidth of the device is in the range of (0.2-43) Hz. The data is transferred through Bluetooth which is having a band power of 2.4 GHz. The average battery life of the device is around 9 hours. All recorded EEG data are digitally filtered in the range of 0.1-30 Hz. This is the frequency range which is used for ERP based studies. Signals are analyzed using MATLAB® version 2014a running on PC with the following configuration: Processor: Intel(R) Core(TM) i3-3240, CPU @ 3.40GHz, RAM: 4.00 GB, System Type: 64-bit Operating System, x64-based processor.

In Emotiv Epoc+ device electrodes are absent at Fz, Cz, Pz and Oz locations. Also, the reference locations in the headset are usually behind the ears that is, approximately at P3/P4 positions. Thus, a significant component of P300 ERP which is prominently detected at the central locations of the scalp [73, 74] gets subtracted from all other channels if we select P3/P4 as reference electrodes. This results in considerable reduction in the magnitude of P300 peak. Therefore, to minimize this effect, we have considered alternate reference locations for collecting data (see Figure 4) and extracted P300 from central location by averaging the central pair namely, O1/O2, F3/F4, AF3/AF4 and P7/P8 [73]. Besides, it has been established in the literature [75], that N100 deflection can be detected at most recording sites, including the occipital, parietal, central and frontal electrode sites. Also, N100 peaks earlier over frontal than posterior regions of the scalp, suggesting distinct neural and/or cognitive correlation [75, 76], and the visual N100 component is usually largest over the occipital region [61]. Hence, keeping these in mind, we have gathered the information about N100 ERP from F3, F4, AF3, AF4, P7, P8, O1 and O2 electrodes. Further, it has also been observed that blink signatures in EEG data are immediately recognizable from the AF3 channel.

3.3. Vigilance Task

In this paper, we used the Mackworth Clock Test [77] implemented in Psychology Experiment Building Language (PEBL) [78] for the vigilance detection experiment. In this task, a participant monitors a red pointer moving circularly in front of a black

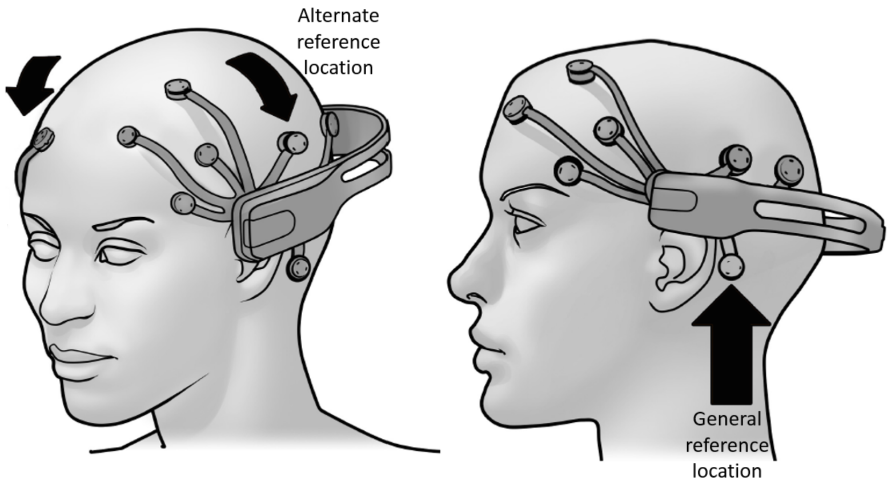


Figure 4: Alternate reference location

background in steps like the seconds' hand of a clock and responds when the clock hand makes a random jump. The probability of clock skipping a normal step/jump is 0.4. Each shift of the pointer depicts a trial. The pointer shifts to a new position throughout the experiment after lapse of one second, such that after at most 60 movements/shifts it completes one full circular round. In a session, whenever the clock skips a normal jump, the user has to promptly press the 'space bar' key. Note that the size of the pointers and the radius of the clock can be varied according to the requirement.

3.4. Subjective Measures

Before performing the vigilance task, each participant was requested to fill their background information along with the pencil-and-paper version of Global Vigor and Affect (GVA) form, whose scale ranges from 0 to 100 [79]. This helps in subjective analysis of affective state (feelings, mood) and level of vigor (alertness, vigilance) of each participant. Moreover, the subjects also filled a Visual Analogue Scale (VAS) to indicate their present mood. The VAS scale ranges from 0 to 10, where '10' signifies a "happy" mood and '0' corresponds to a "sad" mood.

Further, immediately after the completion of the session, the participants expressed their present state using the VAS form. Along with this, the participants also reckoned the task difficulty using the NASA-TLX [80] questionnaire on the scale of 20.

3.5. Procedure

The experiment was carried out in a quiet and isolated room with maintained room temperature, where each participant was seated comfortably. A large 20-inch monitor was placed approximately 65 cm away from the participants for presenting visual stimuli. Initially, to inure each participant, we asked them to relax for a duration of ten minutes. Thereafter, in the next five minutes, we asked participants to fill subjective questionnaires namely VAS and GVA. Through these questionnaires, we assessed the physiological health of participants via their own judgements about various parameters relating to them. After this task, a five minutes' instruction, demonstration and practice session was arranged for each participant, which was followed by baseline EEG data recording. During baseline data recording the participants were asked to sit idle for five minutes with restricted movement of body organs. Besides, during the complete session participants were asked to avoid, as far as possible, movement of any kind except for responding to the target stimuli. After baseline data recording, we performed a 20 minutes' clock test (involving 1200 trials) discussed earlier in Section 3.3. Next, participants were again asked to fill the subjective questionnaires namely VAS and NASA-TLX for assessing the toughness, present mood and effort required during the experiment. Further, a five minutes' baseline data recording was done again to seek the changes in the mental stress/load of the participants, which was followed by a repetition of the clock test with 600 trials for ten minutes. This experiment was conducted once with each participant. Moreover, only a single participant's data was recorded in a day. The data recording was done between 7:00 AM - 10:00 AM as per the availability of the participants. This complete procedure has been graphically shown in Figure 5 for the sake of clarity.

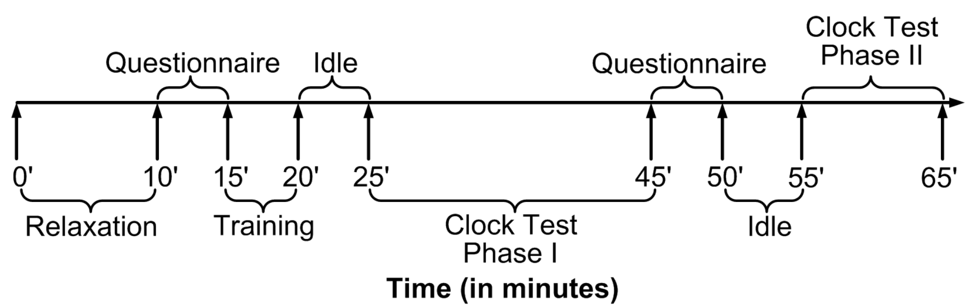


Figure 5: Description of experimental protocol

3.6. Feature Extraction

The extraction of features (ERPs and eyeblink) from EEG involves several steps. These steps have been described in detail in the following:

(i) **ERP Detection**: EEG data is susceptible to noise from various electro-physiological sources. Hence, to remove the noise and for extracting the desired features (ERPs) from EEG, we perform:

  (a) *Filtering*: The recorded raw signals are first pre-processed to remove artifacts of all kinds and to harness crucial information. For this, we resorted to basic filtering process using Chebyshev's high pass filter (having cut off frequency of 0.1 Hz) to remove disturbing components emerging due to breathing and voltage changes in neuronal and non-neuronal artifacts. We also used

Chebyshev's low pass filter (having cut off frequency of 30 Hz) to eliminate noise arising from muscle movements. Besides, we considered a notch filter, with null frequency of 50 Hz, at the recording time to ensure perfect rejection of the strong 50 Hz power supply interference, impedance fluctuation, cable defects, electrical noise, and unbalanced impedances of the electrodes. Further, the processed signals were also inspected visually for the presence of muscle and motion, eye movements and other artifacts. The independent components analysis (ICA) was employed to reject all unqualified data caused by eye blinks.

(b) *Epoch Marking*: In this step, we extract the corresponding event epochs from the EEG signals. This is accomplished by identifying the locations that is, the time instants of stimuli occurrence of the target and the non-target stimuli. This process marks every target and non-target events. Here, the term target events indicate the locations where the clock skips a beat/jump and non-target events indicate the normal ticking of the clock. The window length for each epoch is kept from -500 ms to 1000 ms.

(c) *Baseline Removal*: This is to remove the artifacts arising from low frequency drifts and leading to data skewness. The *baseline removal* also eliminates the overall voltage offset (if any) from the waveforms in each epoch. Besides, it is done to prevent unnecessary rejection of many trials owing to the presence of overall voltage offset. For removing baseline signals, we segmented the epochs representing the target events into 500 ms pre-stimulus and 1000 ms post-stimulus epochs. Then, we evaluated the arithmetic mean of the pre-stimulus data and subtracted it from each value of the considered post-stimulus data to complete the baseline removal process.

(d) *Trial Averaging*: To increase the Signal-to-Noise-Ratio (SNR) of ERPs, we used temporal processing method (ensemble averaging) on large number of trials. In this method, a large number of trials comprising of signals having random Gaussian noise, which is not correlated to the signals and not necessarily periodic although repetitive, are averaged together to enhance the SNR. This gradually prunes the noise from the background. Further, to obtain the recognizable ERP waveforms the post stimulus data are averaged according to the ordinal position of the target stimulus sequence. The remaining epochs are also averaged across the entire non-target stimuli sequence to allow evaluation of non-stimulus response. Next, after obtaining the ERP signals, we identify the N100 (amplitude and latency) and P300 (amplitude and latency). An instance of ERP scalp array obtained from target events is shown in Figure 6. Further, the ERP plot for F4 channel is shown in Figure 7 which clearly indicates the difference between target and non-target events.

(ii) **Eye Blink Detection**: It is well-known that in a normal human-being an eye blink lasts for about 400 milliseconds and has an amplitude of at least 40 μV. Using these two parameters as threshold we detected eye blinks from the EEG signals (see Figure 3), through the AF3 channel of the EEG device, due to its

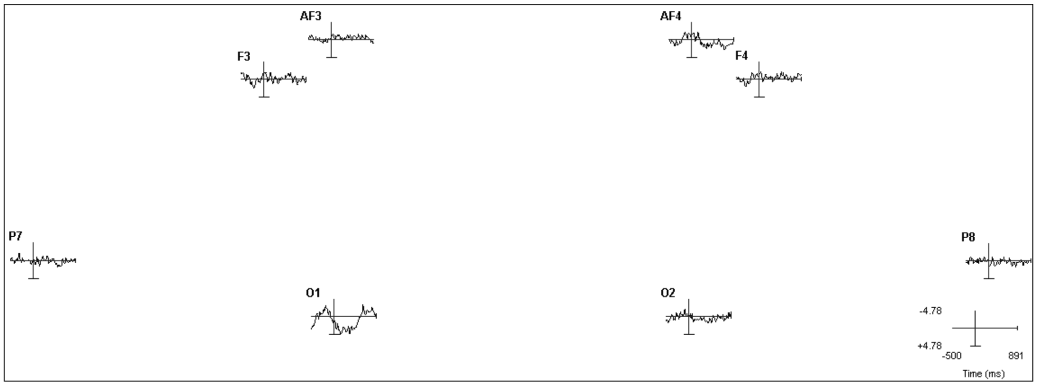


Figure 6: An instance of obtained ERP scalp array for target events

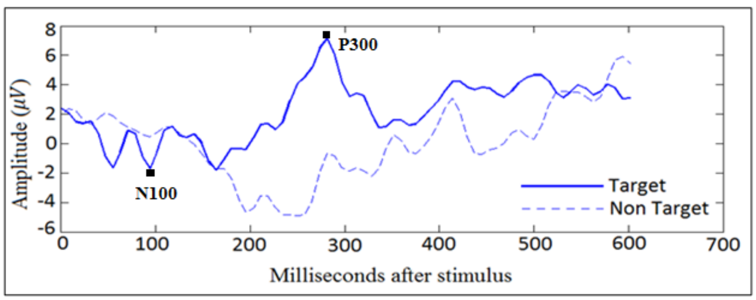


Figure 7: ERP comparison between target and non-target events

prominent presence at this location [81]. This task requires minimization of the false detection of eye blinks, and was carefully performed by dividing the recorded signals (from AF3 channel) into overlapping windows wherein each window had a width of 110 samples.

To minimize the false detection of eye blinks we checked whether a complete eye blink was present in a window or not. If it was successfully detected, it was considered as true eye blink; however, if only a trough was observed in a window then the adjacent window was checked for the presence of its crest. If the crest was also observed then it was regarded as true eye blink and noted, otherwise, it was regarded as a false signal originating due to some noise and was rejected.

3.7. Vigilance Computation

Vigilance assessment is a very complicated process as it is highly influenced by factors such as environment, health and sleep history. The effect of these factors is not always visually observable and can only be inferred from the available physiological information. Moreover, due to the above factors perceptual sensitivity of vigilance declines over the course of time.

In a vigilance detection experiment, a participant responds by tapping a key in case a target stimulus appears on the screen. For this, his/her mind internally processes the information about decision making (that is responding to a target) and thereby eliciting N100 and P300 waveforms. So, by capturing brain activities we can easily and accurately assess the vigilance state of any individual.

Traditional signal processing analyzes events and categorizes them into discrete mutually exclusive categories. However, such form of assessment is not desirable or possible in case of vigilance measurement. In the present work, we subsequently combined P300 and N100 ERPs along with eye blink rate for robustly and accurately characterizing the vigilance level of an individual. To extend the measurement beyond the traditional crisp method, we have chosen fuzzy rule-based technique for its well-known linguistic concept modeling ability. The fusion of the parameters have been done using a fuzzy system, such that it allows for events to be simultaneously present in more than one category; thereby, making the response dimensions continuous. To perform the fuzzy analysis, the following procedure has been followed.

(i) *Fuzzification*: Fuzzification permits the quantification of uncertainty inherent in the response. In our vigilance detection task, three parameters (N100, P300 and Eye blink rate) are taken as input to evaluate the vigilance level of an individual. The three variables which vary with variation in vigilance level are: (i) Elicitation time (t) of N100 and P300, (ii) Amplitude (a) of N100 and P300, and (iii) Blink rate. During fuzzification, these variables are defined linguistically (Mamdani approach) based on the range they cover (refer Table 1). Let us denote P300 as P and N100 as $\mathbb{N}$, then for amplitude, we define three linguistic states namely: Low Amplitude (LA), Medium Amplitude (MA) and High Amplitude (HA). Similarly, the linguistic states for time are classified as: Before Time (BT), Optimum Time (OT) and After Time (AT). Finally, blink rate is categorized into three states such as: Fast Blink (FB), Normal Blink (ηB) and Slow Blink (SB). Now, depending on the amplitude and time, P300 (P) is divided into four fuzzy sub-categories: No P300 (NP), Low P300 (LP), Moderate P300 (MP) and High P300 (HP). Similarly, N100 ($\mathbb{N}$) is divided as: No N100 ($N\mathbb{N}$), Low N100 ($L\mathbb{N}$), Moderate N100 ($M\mathbb{N}$) and High N100 ($H\mathbb{N}$). The above definitions of P300 and N100 signal can be mathematically represented as:

$$
\begin{aligned}
&Z_{a,t} = Y where\\
&Z\ represents\ considered\ ERP\ features,\\
&Z \in \{P, \mathbb{N}\}\\
&a \in \{LA, MA, HA\}\\
&t \in \{BT, OT, AT\}\ and\\
&Y\ is\ the\ set\ of\ all\ possible\ states\ of\\
&\quad considered\ ERP\ features,\\
&Y \in \{NP, LP, MP, HP, N\mathbb{N}, L\mathbb{N}, M\mathbb{N}, H\mathbb{N}\}
\end{aligned}
$$

Figure 8, shows the relationship between amplitude and time for N100 and P300 signals. In this fuzzy rule base system, vigilance has been graded into four classes:

Table 1: Input and output value ranges of fuzzy variables

	Input	**Linguistic Value**	**Function**	**Values**
N100	Amplitude	Low	Triangular	[0 0 1]
		Medium		[0.25 2 4]
		High		[2.5 6 6]
	Time	Before	Triangular	[70 70 100]
		Optimum		[90 100 180]
		After		[140 200 200]
P300	Amplitude	Low	Triangular	[0 0 4]
		Medium		[2 5 10]
		High		[6 20 20]
	Time	Before	Triangular	[200 200 270]
		Optimum		[250 312 550]
		After		[500 700 700]
Blink	Time	Fast	Triangular	[0 0 4]
		Normal		[2 5 7]
		Slow		[5 10 10]
ERP	N100	Absence	Triangular	[0 0 1.5]
		Low		[0 2.2 5]
		Moderate		[3.5 6 9]
		High		[8 10 10]
	P300	Absence	Triangular	[0 0 1.5]
		Low		[0 2.2 5]
		Moderate		[3.5 6 9]
		High		[8 10 10]
Vigilance Level	ERP	No	Triangular	[0 0 1.5]
		Low	Triangular	[0 2.2 5]
		Moderate	Triangular	[3.5 6 9]
		High	Triangular	[8 10 10]

No Vigilance (NV), Low Vigilance (LV), Moderate Vigilance (MV) and High Vigilance (HV).

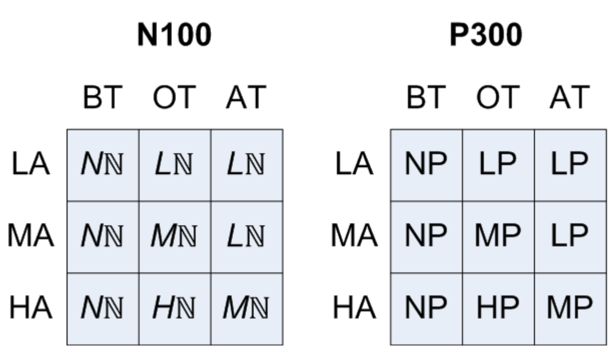


Figure 8: Relationship between amplitude and time for N100 and P300 signals

(ii) *Fuzzy Rule Base*: The designed fuzzy rule base uses the ERP signals and the blink rate. Here, it should be noted that the ERP signals form an intermediate state of the fuzzy system and are fuzzily defined as: No ERP (NE), Low ERP (LE), Moderate ERP (ME) and High ERP (HE). Vigilance determination is accomplished using two level fuzzy rules. In the first level, from the N100 and P300 signals, intensity of ERP signals is identified and next, using the intensity of ERP signals and the blink rate, vigilance level is determined. To clarify the notion, the fuzzy inference system for vigilance estimation is shown in Figure 9, and the overall fuzzy rule base matrix is shown in Figure 10. Besides, the proposed logic for calculating vigilance from the ERP signals and blink rate is given in Eq. ii.

$$Vigilance = (P300 \vee N100) \wedge Blink\ Rate$$

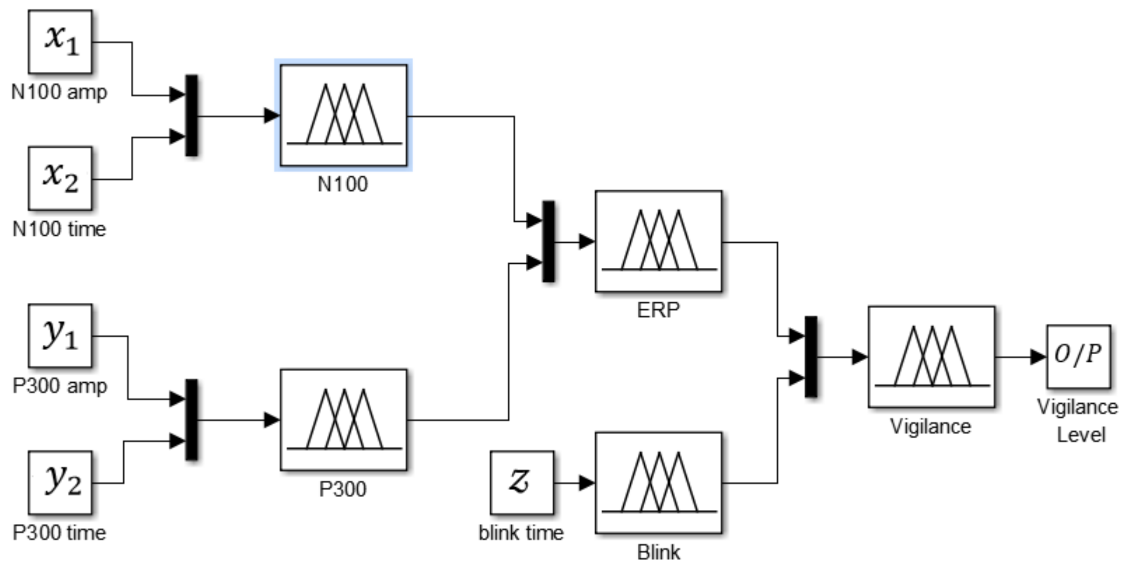


Figure 9: Fuzzy inference system for vigilance estimation

ERP

	$N\mathbb{N}$	$L\mathbb{N}$	$M\mathbb{N}$	$H\mathbb{N}$
NP	NE	LE	ME	HE
LP	LE	LE	ME	HE
MP	ME	ME	ME	HE
HP	HE	HE	HE	HE

Vigilance

	FB	ηB	SB
NE	NV	NV	NV
LE	NV	LV	LV
ME	LV	MV	HV
HE	LV	MV	HV

Figure 10: Fuzzy rule base matrix

The logic behind Eq. ii is: under the effect of target stimulus, both P300 and N100 are elicited; however, the environmental noise deteriorates both P300 and N100. In many cases, these ERPs become completely invisible or either of them may be present with very low magnitude. In order to address this issue, we perform *OR* operation between P300 and N100, so as to obtain values from either of the two ERPs. Next, we use *AND* operator between the obtained intermediate result and the blink rate (which is independent of ERPs) to quantify the vigilance. The rule base contains a total of 48 rules for all possible instances. Now, at any particular instance (that is, a given condition or input), membership values along with rule strength are computed.

(iii) *Defuzzification*: To extract deeper insight from the results obtained, the fuzzified values are defuzzified into crisp forms. In this paper, we have used the Mean of Maximum (MoM) method to obtain the crisp values. The MoM strategy generates a quantity which represents the mean value of all outputs, whose membership functions reach the maximum [82]. This method is known to provide the most plausible result. In other words, the fuzzy controller uses the typical value of the consequent term of the most valid rule as the crisp output value.

$$X = \sum_{i=1}^{n} \frac{w_i}{n}$$

where,

$$\{w_i | \mu_c(w_i) \geq \mu_c(w_j), w_i, w_j \in W, w_i \neq w_j\}$$

and n is the number of such support values.

4. Results and Discussion

To establish the correlation among ERPs, eye blink and vigilance activity, and to obtain a numerical relationship among them, we performed each experiment in two phases. In the first phase, a continuous data recording of brain signals was done for 20 minutes. In the next phase, data recording was done for 10 minutes. For accurately observing various phenomenon recorded in EEG signals, the data recorded in the two phases of the experiment was further divided in equal segments of 2 minutes, such that the data recorded in the first phase and second phase comprises of 10 and 5 equal parts, respectively. Besides, the other analysis carried out by us and the results obtained therein are discussed hereunder:

4.1. Behavioural Analysis

(a) *Visual Analogue Scale (VAS)*

For the vigilance experiment, it is important to observe changes in the mood of the participants before and after the experiment. Hence, we performed a subjective analysis using VAS. Next, we set the hypotheses as follows: H_0 = The null hypothesis: the mood of each participant remains same throughout the experiment; H_a = The alternate hypothesis: when the mood of each participant before and after the experiment differs significantly, and performed a paired t-test. The results at significance level 0.05 indicated that there is a significant difference between the moods of the participants prior to experiment and post experiment (refer Figure 11). This is probably due to the high cognitive load involved in the experiment requiring sustained attention on the moving pointer in the clock test.

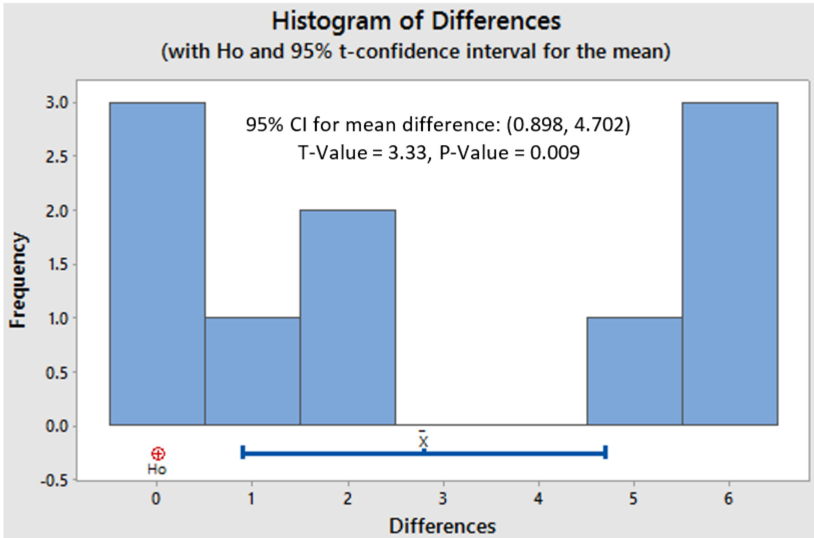
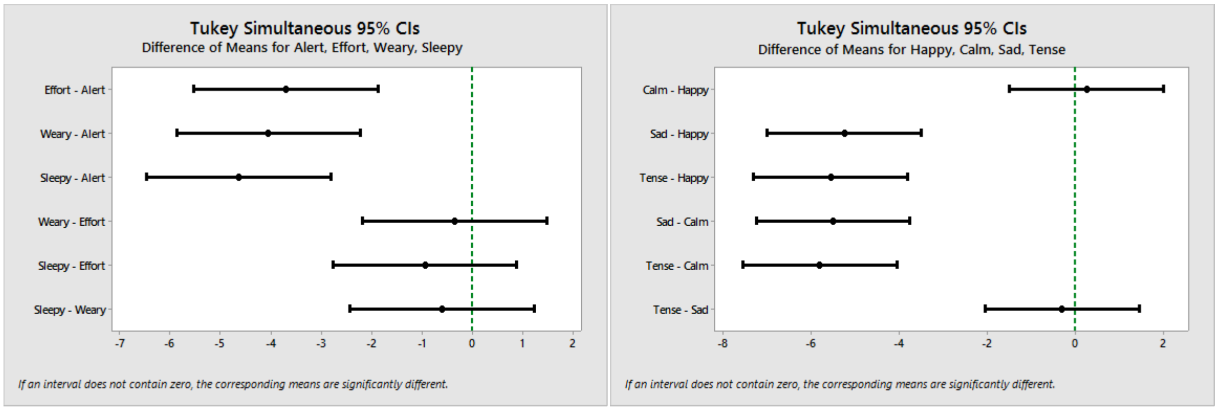


Figure 11: Histogram plot of the paired t-test for the VAS scale

(b) *Global Vigor and Affect Scale (GVA)*
We utilized one-way ANOVA and Tukey's pairwise comparison of means of factors for analysing Global Vigor (GV) and Global Affect (GA) subjective ratings. The GV (mean, $\mu = 74.8$ and standard deviation, $\sigma = 0.86$) evaluation involves factors namely, *alert, effort, weary and sleepy*; whereas, in GA, *happy, calm, sad and tense* are the contributing elements. Results obtained from GV suggests that all contributing factors are significant at $\alpha = 5\%$ (significance level), wherein factors have μ and σ as follows: alert ($\mu = 6.750$, $\sigma = 1.620$), effort ($\mu = 3.050$, $\sigma = 1.499$), weary ($\mu = 2.700$, $\sigma = 1.418$) and sleepy ($\mu = 2.100$, $\sigma = 1.524$). The post-hoc Tukey's comparison test (refer to Figure 12 (a)) revealed that alert factor at $p < 0.001$ is highly significant than effort, weary and sleepy factors.
Likewise, the factors involved in GA ($\mu = 52.825$ and $\sigma = 0.89$) are significant at $\alpha = 5\%$, wherein factors have μ and σ as follows: happy ($\mu = 7.450$, $\sigma = 1.212$), calm ($\mu = 6.900$, $\sigma = 2.234$), sad ($\mu = 2.200$, $\sigma = 1.549$) and tense ($\mu = 1.900$, $\sigma = 1.912$). Further, the Tukey's comparison test (refer to Figure 12 (b)) revealed that factor happy is highly significant than sad and tense at $p < 0.001$; whereas, calm is significant than sad and tense at $p < 0.001$.

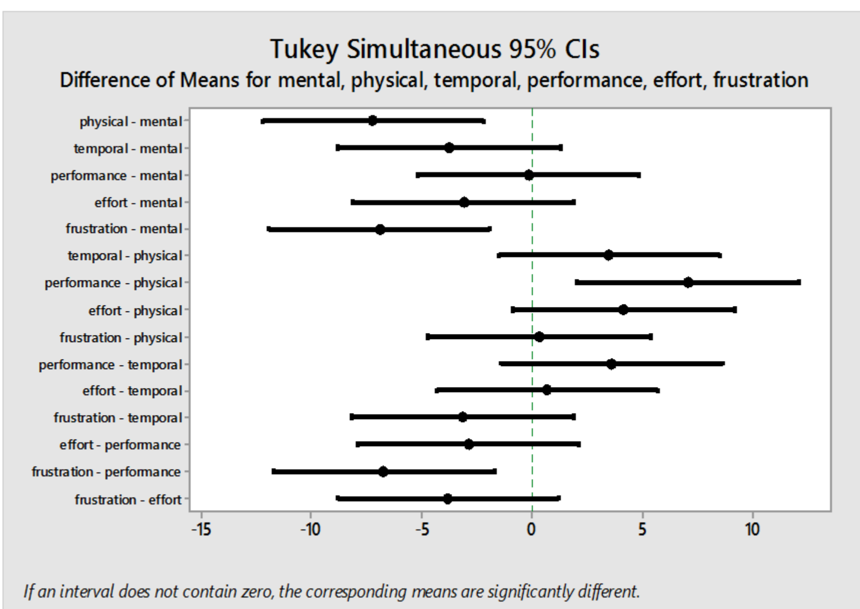
(c) *NASA-TLX*
Similar to GVA, here, we used one-way ANOVA and Tukey's pairwise comparison test for multiple mean comparisons of NASA-TLX subjective load index ($\mu = 12.09$ and $\sigma = 1.69$). The results reveal that the factors considered are significant at $\alpha = 5\%$ (significance level). The mean and standard deviation for each of the factors are as follows: mental demand ($\mu = 14.000$, $\sigma = 2.981$), physical demand ($\mu = 6.76$, $\sigma = 4.86$), temporal demand ($\mu = 10.22$, $\sigma = 4.05$), performance ($\mu = 13.80$, $\sigma = 3.38$), effort ($\mu = 10.88$, $\sigma = 3.26$), frustration ($\mu = 7.06$, $\sigma = 3.91$). Further, Tukey's pairwise comparisons (refer to Figure 13) is used for grouping of significant



(a) Difference mean plot for global vigor factors (b) Difference mean plot for global affect factors

Figure 12: Difference mean plot for Global Vigor and Affect Scale (GVA)

and non-significant comparisons. From the assessment of NASA-TLX, we observed that the mental demand and performance are highly significant factors; effort and temporal demand are moderately significant factors; and frustration and physical demand are least significant factors. We also observed that mental demand is more significant to both physical demand at $p < 0.001$ and frustration at $p < 0.002$. Also, it is observed that physical demand is more significant than performance at $p < 0.002$, while, performance is more significant than frustration at $p < 0.003$.



Tukey Pairwise Comparisons

Grouping Information Using the Tukey Method and 95% Confidence

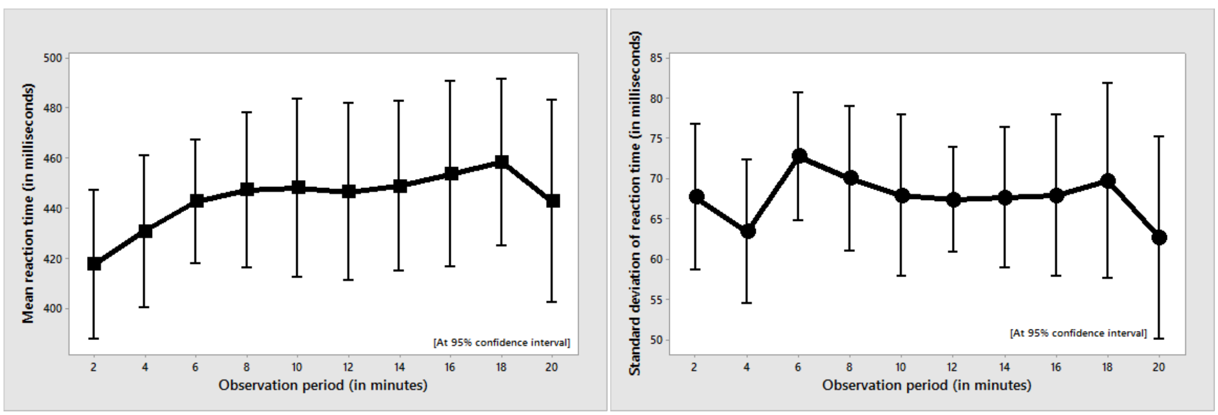
Factor	N	Mean	Grouping
mental	10	14.000	A
performance	10	13.80	A
effort	10	10.88	A B
temporal	10	10.22	A B
frustration	10	7.06	B
physical	10	6.76	B

Means that do not share a letter are significantly different.

Figure 13: Difference mean plot for factors involved in NASA-TLX questionnaire

4.2. Reaction Time Analysis

The mean reaction time taken by each user for correctly detecting and responding to the critical stimuli during the first phase of the experiment is plotted in Figure 14. We can clearly observe from Figure 14 (a) that the mean response time rapidly increases initially for few minutes of the experiment, then it becomes almost stable indicating that the participants becomes accustomed to the task. Later parts of the first phase again show an increasing trend of the mean reaction time, which is due to the mental fatigue; but, strangely during the last two-minutes of the first phase, mean reaction time decreased significantly. The reason behind this decrement in the reaction time during the last two-minutes of the first phase is against the intuitive behaviour and was observed in case of each participant. The plot of the standard deviation of reaction times, shown in Figure 14 (b), obtained from different participants during the first phase indicates that there is little deviation in the reaction times of different participants. This suggests that the clock test affects all participants in similar way and induces similar mental demand from each participant.

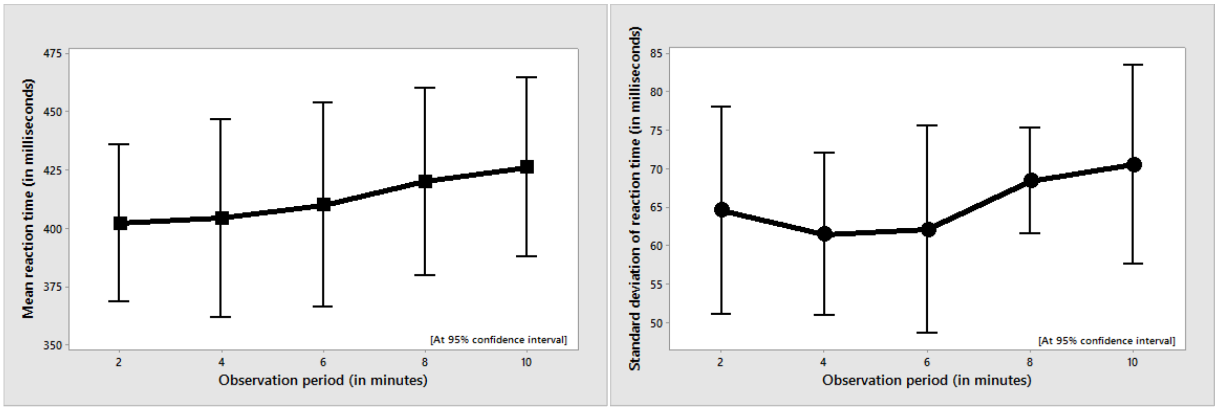


(a) Mean reaction time

(b) Standard deviation of the reaction time

Figure 14: Reaction time during the first phase of the experiment

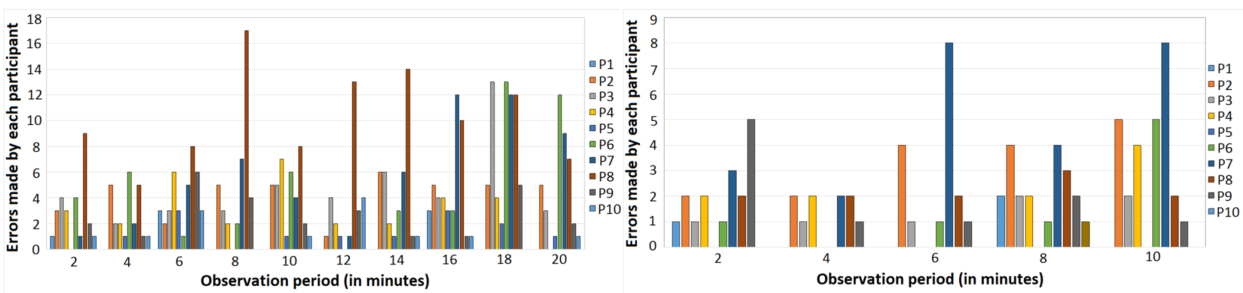
The mean reaction time during the second phase of the experiment has been plotted in Figure 15. The trend-line starts at a lower level in comparison to the starting reaction time of the first phase. This happens mainly due to: a) the 5 minutes rest given to each participant before beginning the second phase, and b) the participants became accustomed to the task which they were performing. Besides, this phase also shows an increasing mean reaction time due to monotonous nature of the job under consideration. Through this we can infer that if a person/operator takes short spans of rest while continuously performing any monotonous task the reaction time to any alarming situation can be considerably reduced. The plot of the standard deviation of reaction times are obtained from different participants during the second phase, shown in Figure 15 depicts that there is not much deviations in the reaction times of different participants.



(a) Mean reaction time (b) Standard deviation of the reaction time

Figure 15: Reaction time during the second phase of the experiment

The plots shown in Figure 16 display the errors made by each participant during the first and second phase of the experiment, respectively.

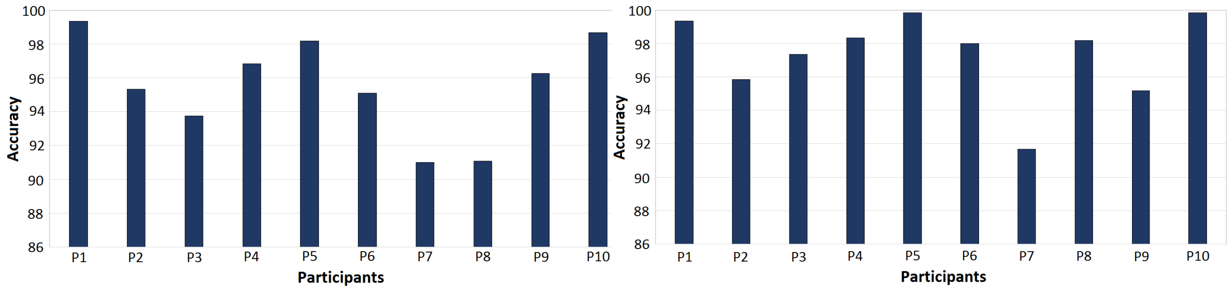


(a) Errors in each 2 minute duration of the first phase of vigilance task (b) Errors in each 2 minute duration of the second phase of vigilance task

Figure 16: Number of errors made by the participants

To evaluate the the performance of the participants, accuracy is used as an evaluation criterion. For estimating the accuracy of detection, the recorded EEG data is divided into four sub-categories defined as true alarm (TA), true skip (TS), false alarm (FA) and false skip (FS), where true alarm represents correct identification of target stimuli, true skip represents correct identification of non-target stimuli, false alarm represents incorrect key pressed at non-targets and false skip represents non-identification of the target stimuli. Based on these data, the accuracy is calculated using the formula given in equation 1. The plots of accuracy of detection for both phases of the experiment can be seen in Figure 17.

$$Accuracy = \frac{TA + TS}{TA + TS + FA + FS} \tag{1}$$



(a) Detections in the first phase of vigilance task

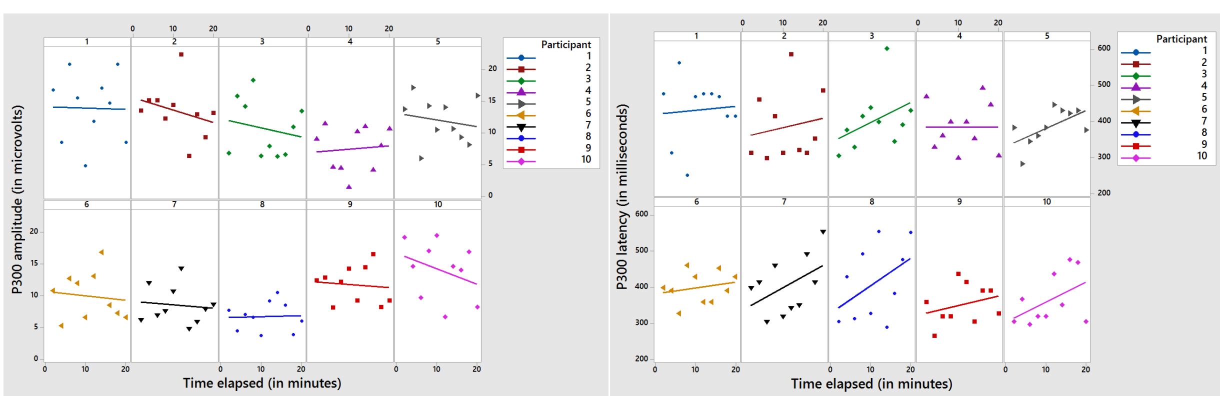
(b) Detections in the second phase of vigilance task

Figure 17: Percentage of accurate detections made by the participants

4.3. P300 Analysis

As already discussed in previous sections, the level of vigilance of an operator or an individual varies with passing time. Hence, to carefully study such a variation we observed the variation of P300 amplitude of each individual within small intervals of two minutes, obtained by slicing the complete time interval of both experimental phases (that is, I and II) into equal slots of two minutes duration.

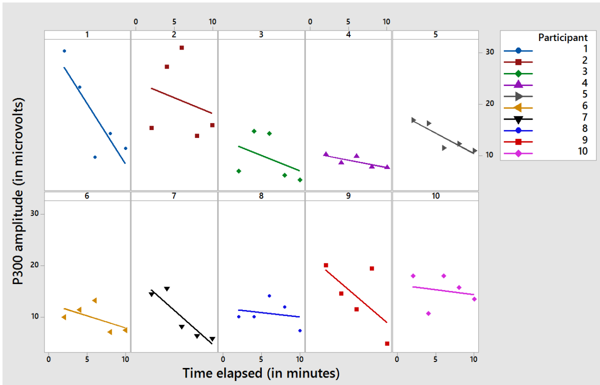
From the first phase (that is, 20 minutes clock test) of the experiment, we observed that for each participant, P300 amplitude either decreased or remained steady with the passing time, see Figure 18 (a). Besides, we also observed that with passing time the latency in invocation of P300 increased for almost all participants, see Figure 18 (b). This signifies that both P300 ERP and vigilance are time dependent quantities and their amplitude falls with passing time. Further, in the second phase of the experiment (that is, 10 minutes clock test), which was performed after a short period of rest of 5 minutes, we observed similar behaviour, as was observed in first phase, of P300 amplitude and latency (see Figure 19).



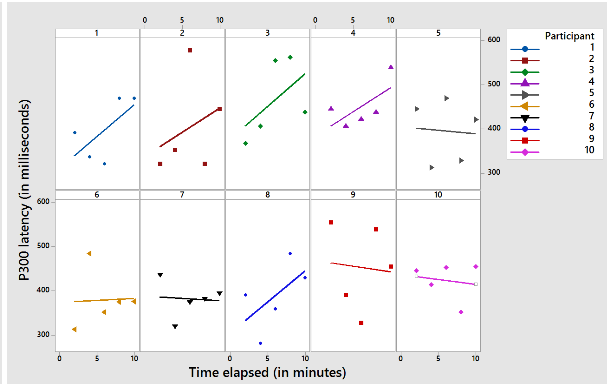
(a) P300 amplitude variation in Phase I

(b) P300 latency variation in Phase I

Figure 18: Analysis of 20 minutes clock test

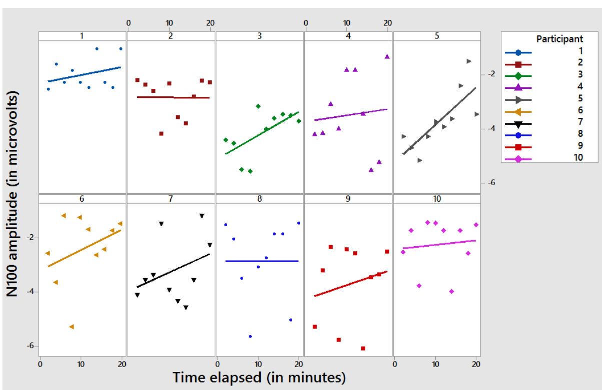


(a) P300 amplitude variation in Phase II

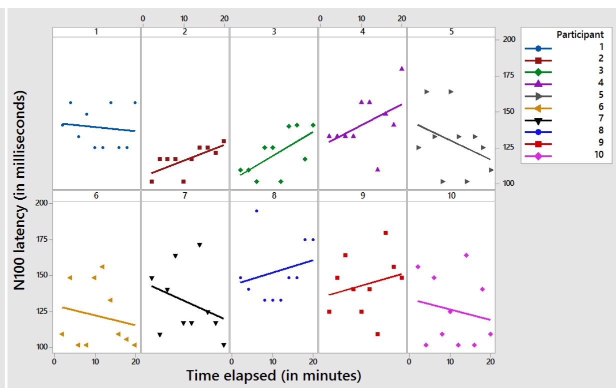


(b) P300 latency variation in Phase II

Figure 19: Analysis of 10 minutes clock test

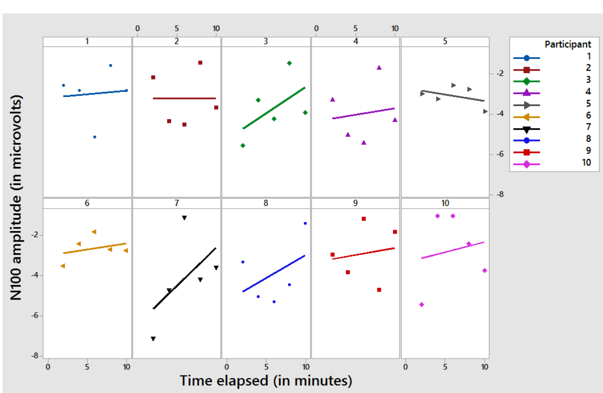


(a) N100 amplitude variation in Phase I

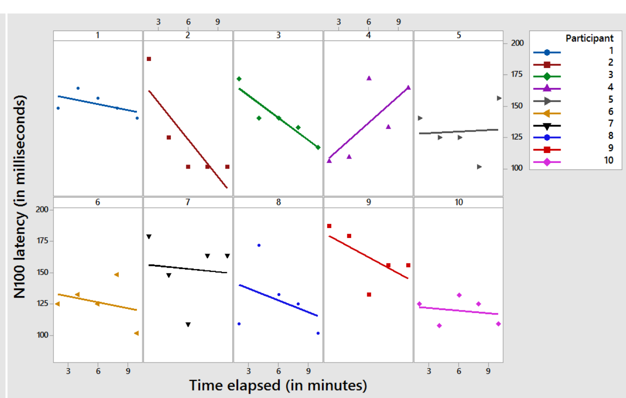


(b) N100 latency variation in Phase I

Figure 20: Analysis of 20 minutes clock test



(a) N100 amplitude variation in Phase II



(b) N100 latency variation in Phase II

Figure 21: Analysis of 10 minutes clock test

4.4. N100 Analysis

N100 ERP is associated with an individual's pre-attention and perception. It usually affects neural activity in the human brain while performing a discrimination task.

Further, it is known that N100 amplitude has higher negative deflection for locations where stimuli are successfully attended and vice-versa for unattended locations [83], [84]. Besides, N100 ERP depict a small decrement in amplitude after several minutes due to repetition of similar stimuli. Thus, to fruitfully study these phenomenon, we analysed N100 component in both the phases of the experiment, wherein we observed that N100 amplitude either decreases or remains steady with passing time (see Figure 20 (a) and 21 (a)). However, for N100 latency no particular trend was observed (refer Figure 20 (b) and 21 (b)).

4.5. Calculation of Vigilance through our proposed Fuzzy Rule-based System

After processing the EEG signals, thereby removing the inherent noise, we locate the P300 and N100 peaks, and extract their respective amplitudes and latency time. We also note the number of eye-blinks and their corresponding intervals. Then, we feed this information in eq. ii of Fuzzy inference system for vigilance estimation (see Figure 9). The fuzzy rules utilized for quantifying vigilance are already discussed in Figure 8 and Figure 10. The numeric evaluation of vigilance, through fuzzy rule-base, for each participant has been done (for every two minutes interval) for both phases of the experiment. The obtained results are tabulated in Table 2 and Table 3. Besides, the overall mean and standard deviation of each variable (N100, P300 and eye blink) during the entire Phase I and Phase II of the experiment have been tabulated in Table 4 and 5. On comparison of the fuzzy output obtained from each participant (refer Table 2 and 3), it can be observed that for participant 3, 4 and 9, the vigilance level in phase I was higher in comparison to phase II, while for participant 6 and 8 the scenario was vice-versa and for the remaining participants the level remained consistent in both the phases.

Table 2: Variation of vigilance for every two minute interval in Phase I

Participant	**Vigilance value within interval**										**Mean Vigilance**
	(0-2) min	***(2-4) min***	***(4-6) min***	***(6-8) min***	***(8-10) min***	***(10-12) min***	***(12-14) min***	***(14-16) min***	***(16-18) min***	***(18-20) min***	
P1	10	9.75	6	10	10	6	10	10	10	10	**9.175**
P2	6.75	9.8	6	10	6	10	10	6	6	9.85	**8.04**
P3	9.9	9.85	9.85	9.85	9.85	9.7	9.75	9.9	9.9	10	**9.855**
P4	6	9.9	10	9.9	9.75	9.95	9.85	6.05	9.75	2.4	**8.355**
P5	2.25	10	9.9	9.75	9.95	2.25	9.9	6	6	6.05	**7.205**
P6	10	9.85	10	9.95	10	10	10	10	2.25	6	**8.805**
P7	9.85	10	10	10	10	9.9	10	9.9	9.9	9.85	**9.94**
P8	10	6	9.9	9.9	6	2.4	9.95	6	10	2.4	**7.255**
P9	9.95	10	2.45	9.9	10	10	9.95	10	10	10	**9.225**
P10	6.5	9.8	9.85	10	9.9	10	6	6	6	6	**8.005**

4.6. Validation of the proposed Fuzzy Model

To validate the accuracy and efficiency of the proposed model, we compared the mean vigilance level obtained by averaging all vigilance data, of 2 minute slices, of each individual with the target detection accuracy (from clock test) of each individual. To accomplish this task, we divide the accuracy levels into four bands, namely: a) very low accuracy - if the value is $\geqslant 0$ and < 30 percent; b) low accuracy - if the value is $\geqslant 30$ and

Table 3: Variation of vigilance for every two minute interval in Phase II

Participant	**Vigilance value within interval**					**Mean Vigilance**
	(0-2) min	***(2-4) min***	***(4-6) min***	***(6-8) min***	***(8-10) min***	
P1	10	2.75	9.85	7.5	9.9	**8**
P2	2.4	9.85	9.85	10	9.9	**8.4**
P3	7.25	6	6	6.2	9.9	**7.07**
P4	2.25	9.85	10	7.25	9.8	**7.83**
P5	6	10	9.95	9.75	9.85	**9.11**
P6	10	10	10	10	9.95	**9.99**
P7	10	9.85	10	10	9.95	**9.96**
P8	7.25	9.85	6	9.9	10	**8.6**
P9	2.45	2.4	9.85	9.85	10	**6.91**
P10	9.95	10	2.25	10	9.95	**8.43**

Table 4: Fuzzy vigilance calculation of Phase I experiment

Phase I Clock Test (20 minutes)												
Participant	**N100 amplitude**		**N100 latency**		**P300 amplitude**		**P300 latency**		**No. of Blinks**		**Vigilance (through fuzzy rule-base)**	
	Mean	*S. D.*	*Mean*	*S. D.*	*Mean*	*S. D.*	*Mean*	*S. D.*	*Mean*	*S. D.*	*Mean*	*S. D.*
P1	-1.9829	0.57424	139.1	14.186	14.37	5.07304	432.1	90.5239	10.3	6.51579	9.175	1.675186557
P2	-2.834	0.7396	117.3	9.28858	13.4	4.15711	385.3	97.7561	15.2	6.97296	8.04	2.005797154
P3	-4.1458	0.84732	121	15.6261	10.61	4.49522	402.3	82.4673	10.1	4.7481	9.855	0.0831665
P4	-3.4742	1.44458	142.2	19.0734	8.437	5.44178	384.4	68.0988	13.5	6.8678	8.355	2.634646297
P5	-3.7026	1.07791	128.9	22.1734	11.92	3.59605	385.2	49.6765	15.4	8.14043	7.205	3.156866414
P6	-2.384	1.26757	121.5	22.3937	9.941	3.70311	400	43.3823	2.9	6.77331	8.805	2.620586236
P7	-4.2045	3.71946	131.3	23.7655	8.717	3.09416	405.5	79.7056	3.2	2.65832	9.94	0.065828059
P8	-2.8605	1.46003	153	21.5989	6.733	2.27298	412.2	102.837	14.7	6.86456	7.255	3.13035763
P9	-3.68748	1.44836	143.8	20.5755	11.73	2.9064	353.1	54.2341	4.8	2.52982	9.225	2.380738681
P10	-2.23856	0.94677	125.8	24.5457	14.03	4.48668	389.9	88.66	19	10.8115	8.005	2.01445471

Table 5: Fuzzy vigilance calculation of Phase II experiment

Phase II Clock Test (10 minutes)												
Participant	**N100 amplitude**		**N100 latency**		**P300 amplitude**		**P300 latency**		**No. of Blinks**		**Vigilance (through fuzzy rule-base)**	
	Mean	*S. D.*	*Mean*	*S. D.*	*Mean*	*S. D.*	*Mean*	*S. D.*	*Mean*	*S. D.*	*Mean*	*S. D.*
P1	-3.1198	1.6518	151.6	8.94164	17.78	8.77905	396.9	70.6531	9.6	7.19722	8	3.116287856
P2	-2.62504	2.13999	123.5	37.2058	20.67	7.87324	403.1	110.419	10.2	8.25833	8.4	3.354660937
P3	-3.7002	1.49647	140.6	19.9254	9.425	4.64824	465.6	88.4832	21.4	9.93982	7.07	1.664932431
P4	-4.1648	1.61156	136.7	30.525	8.784	1.15045	450	52.0011	8	5.52268	7.83	3.322009934
P5	-3.2872	0.92644	129.7	20.3725	13.55	2.80776	385.9	69.3685	14.8	4.91935	9.11	1.74119212
P6	-2.6282	1.27052	126.6	16.91	9.825	2.61004	365.6	72.3295	5.6	3.20936	9.99	0.02236068
P7	-4.1234	2.16166	153.1	26.839	10.07	4.59565	378.1	41.5647	5.6	4.66905	9.96	0.065192024
P8	-3.893	1.59709	128.1	27.4645	10.72	2.51113	389.1	76.2162	5.6	3.36155	8.6	1.857081043
P9	-3.407	2.08605	162.5	21.6784	14.09	6.2778	446.9	97.5062	7.6	4.39318	6.91	4.094722213
P10	-3.1252	2.32441	119.8	10.78	13.05	3.0376	401.6	51.3786	4.6	3.1305	8.43	3.45481548

< 50 percent c) moderate accuracy - if the value is $\geqslant 50$ and $\leqslant 80$ percent and d) high accuracy - if the value is $\geqslant 80$ and $\leqslant 100$ percent. The respective bands for vigilance are already discussed in Section 3.7. The obtained values are tabulated for comparison and can be seen in Table 6. It is clearly evident from Table 6 that the values obtained from fuzzy model suitably mimic the accuracy, thereby vigilance in both phases of the

Table 6: Comparison of vigilance with accuracy

Participant	20 minutes Clock Test				10 minutes Clock Test			
	Fuzzy Result (numeric)	***Fuzzy Vigilance Level***	***Clock Test Accuracy (%)***	***Accuracy Level***	***Fuzzy Result (numeric)***	***Fuzzy Vigilance Level***	***Clock Test Accuracy (%)***	***Accuracy Level***
P1	9.175	High	98.53043478	High	8	High	98.83861237	High
P2	8.04	High	91.10715836	High	8.4	High	93.28183203	High
P3	9.855	High	90.2249373	High	7.07	Moderate	79.41550758	Moderate
P4	8.355	High	93.3789222	High	7.83	Moderate	79.21559895	Moderate
P5	7.205	**Moderate**	97.23231964	**High**	9.11	High	100	High
P6	8.805	High	89.5006181	High	9.99	High	96.19246124	High
P7	9.94	High	88.17685928	High	9.96	High	90.40641873	High
P8	7.255	Moderate	79.75911231	Moderate	8.6	High	95.49763562	High
P9	9.225	High	94.20888276	High	6.91	Moderate	80.82084969	Moderate
P10	8.005	High	97.29157218	High	8.43	High	99.63636364	High

experiment. From the results shown in Table 6, it can also be observed that there is only one instance in which the obtained fuzzy vigilance level differs from the achieved accuracy of the participant, and found that the overall accuracy of our fuzzy model is 95 %. To search the reason behind 5 % inaccuracy, we observed the input parameters of the concerned participant. We verified that the associated P300 latency with the participant was quite high, due to which the fuzzy rule-base system resulted in low vigilance value for the participant.

5. Conclusion

This paper presented a new vigilance estimation method using EEG signals, recorded with the help of Emotiv Epoc+, and fuzzy rule-base. Through this work we achieved multiple objectives: First, we analysed the mood and stress level of each participant with the help of subjective analysis; Second, we extracted ERPs (N100 and P300) and eye blinks from the recorded EEG signals and established the correlation between the ERPs, eye blinks and vigilance; Third, with the help of our proposed fuzzy logic we increased the credibility of the vigilance estimation, which in earlier works used to be mostly qualitative due to the uncertainty in the EEG signal classification and indicated mere presence or absence; Fourth, we validated the performance of our proposed fuzzy model against the target detection accuracy and found that the average estimation accuracy of our fuzzy model is 95%.

According to the results obtained, we judged that the proposed fuzzy vigilance estimation method performs effectively with EEG signals and can be regarded to be as good as an expert's opinion. Hence, the method can be instrumental to predict an individual's vigilance in real-time.

6. References

[1] Davies D R and Parasuraman R 1982 *The psychology of vigilance* (Academic Pr)
[2] Parasuraman R and Yantis S 1998 *The attentive brain* (Mit Press Cambridge, MA)
[3] Shingledecker C, Weldon D E, Behymer K, Simpkins B, Lerner E, Warm J, Matthews G, Finomore V, Shaw T and Murphy J S 2010 *Human factors issues in combat identification* 47–66

[4] Warm J S, Parasuraman R and Matthews G 2008 *Human Factors: The Journal of the Human Factors and Ergonomics Society* **50** 433–441

[5] Kecklund G and Akerstedt T 2004 *INFORMATION SOCIETY* **1** 1–2

[6] Damousis I G, Tzovaras D and Strintzis M G 2009 *Personal and Ubiquitous Computing* **13** 43–49

[7] Sigari M H 2009 Driver hypo-vigilance detection based on eyelid behavior *2009 Seventh International Conference on Advances in Pattern Recognition* pp 426–429

[8] Bergasa L M, Nuevo J, Sotelo M A, Barea R and Lopez M E 2006 *IEEE Transactions on Intelligent Transportation Systems* **7** 63–77

[9] McIntire L K, McIntire J P, McKinley R A and Goodyear C 2014 Detection of vigilance performance with pupillometry *Proceedings of the Symposium on Eye Tracking Research and Applications* (ACM) pp 167–174

[10] McIntire L K, McKinley R A, Goodyear C and McIntire J P 2014 *Applied ergonomics* **45** 354–362

[11] Körber M, Cingel A, Zimmermann M and Bengler K 2015 *Procedia Manufacturing* **3** 2403–2409

[12] Shaw T H, Funke M E, Dillard M, Funke G J, Warm J S and Parasuraman R 2013 *Brain and Cognition* **82** 265–273

[13] Vaseashta A and Khudaverdyan S 2013 *Advanced sensors for safety and security* (Springer)

[14] Boon-Leng L, Dae-Seok L and Boon-Giin L 2015 Mobile-based wearable-type of driver fatigue detection by gsr and emg *TENCON 2015-2015 IEEE Region 10 Conference* (IEEE) pp 1–4

[15] Lee B G, Park J H, Pu C C and Chung W Y 2016 *IEEE Sensors Journal* **16** 242–253

[16] Zhang A and Liu F 2012 Drowsiness detection based on wavelet analysis of ecg and pulse signals *2012 5th International Conference on BioMedical Engineering and Informatics* pp 491–495

[17] Park H, Oh S and Hahn M 2009 Drowsy driving detection based on human pulse wave by photoplethysmography signal processing *Proceedings of the 3rd International Universal Communication Symposium* (ACM) pp 89–92

[18] Bogler C, Mehnert J, Steinbrink J and Haynes J D 2014 *PLoS One* **9** e101729

[19] Harrivel A R, Weissman D H, Noll D C and Peltier S J 2013 *Frontiers in human neuroscience* **7** 861

[20] Tana M G, Montin E, Cerutti S and Bianchi A M 2010 *Computational intelligence and neuroscience* **2010** 3

[21] Gu J N, Liu H J, Lu H T and Lu B L 2011 *An Integrated Hierarchical Gaussian Mixture Model to Estimate Vigilance Level Based on EEG Recordings* (Berlin, Heidelberg: Springer Berlin Heidelberg) pp 380–387 ISBN 978-3-642-24955-6

[22] Choi Y, Kwon N, Lee S, Shin Y, Ryo C Y, Park J and Shin D 2014 *Computational and mathematical methods in medicine* **2014**

[23] Yu H, Shi L C and Lu B L 2007 Vigilance estimation based on eeg signals *Proceedings of IEEE/ICME International Conference on Complex Medical Engineering (CME2007)*

[24] Sauvet F, Bougard C, Coroenne M, Lely L, Beers P V, Elbaz M, Guillard M, Lger D and Chennaoui M 2014 *IEEE Transactions on Biomedical Engineering* **61** 2840–2847 ISSN 0018-9294

[25] Yu H, Lu H, Ouyang T, Liu H and Lu B L 2010 Vigilance detection based on sparse representation of eeg *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology* pp 2439–2442 ISSN 1094-687X

[26] Zhang Z, Luo D, Rasim Y, Li Y, Meng G, Xu J and Wang C 2016 *Sensors* **16** ISSN 1424-8220 URL `http://www.mdpi.com/1424-8220/16/2/242`

[27] Zhang X, Li J, Liu Y, Zhang Z, Wang Z, Luo D, Zhou X, Zhu M, Salman W, Hu G and Wang C 2017 *Sensors* **17** ISSN 1424-8220 URL `http://www.mdpi.com/1424-8220/17/3/486`

[28] Yildiz A, Akin M, Poyraz M and Kirbas G 2009 *Expert Systems with Applications* **36** 7390–7399

[29] Zheng W L and Lu B L 2017 *Journal of Neural Engineering* **14** 026017 URL `http://stacks.iop.org/1741-2552/14/i=2/a=026017`

[30] Reinerman-Jones L, Matthews G and Mercado J E 2016 *Safety science* **88** 97–107

[31] Akin M, Kurt M B, Sezgin N and Bayram M 2008 *Neural Computing and Applications* **17** 227–236 ISSN 1433-3058 URL `http://dx.doi.org/10.1007/s00521-007-0117-7`

[32] Sun Y and Yu X B 2014 *IEEE journal of biomedical and health informatics* **18** 1932–1939

[33] Wong C W, Olafsson V, Tal O and Liu T T 2013 *Neuroimage* **83** 983–990

[34] Czisch M, Wehrle R, Harsay H A, Wetter T C, Holsboer F, Sämann P G and Drummond S 2012 *Frontiers in neurology* **3** 67

[35] Sengupta A, Dasgupta A, Chaudhuri A, George A, Routray A and Guha R 2017 *IEEE Transactions on Neural Systems and Rehabilitation Engineering* **PP** 1–1 ISSN 1534-4320

[36] Helton W S and Russell P N 2015 *Cognition* **134** 165–173

[37] Smit A S, Eling P A and Coenen A M 2004 *Acta psychologica* **115** 35–42

[38] Li Y, Pan J, Long J, Yu T, Wang F, Yu Z and Wu W 2016 *Proceedings of the IEEE* **104** 332–352 ISSN 0018-9219

[39] Amiri S, Rabbi A, Azinfar L and Fazel-Rezai R 2013 A review of p300, ssvep, and hybrid p300/ssvep brain- computer interface systems *Brain-Computer Interface Systems - Recent Progress and Future Prospects* ed Fazel-Rezai R (Rijeka: InTech) chap 10 URL `http://dx.doi.org/10.5772/56135`

[40] Amiri S, Fazel-Rezai R and Asadpour V 2013 *Advances in Human-Computer Interaction* **2013** 1

[41] Oikonomou V P, Liaros G, Georgiadis K, Chatzilari E, Adam K, Nikolopoulos S and Kompatsiaris I 2016 *arXiv preprint arXiv:1602.00904*

[42] Zhu D, Bieger J, Molina G G and Aarts R M 2010 *Computational intelligence and neuroscience* **2010** 1

[43] Venturini R, Lytton W W and Sejnowski T J 1992 Neural network analysis of event related potentials and electroencephalogram predicts vigilance *Advances in neural information processing systems* pp 651–658

[44] Parasuraman R, Warm J S and Dember W N 1987 Vigilance: Taxonomy and utility *Ergonomics and human factors* (Springer) pp 11–32

[45] Parasuraman R 1980 *Biological psychology* **11** 217–233

[46] O'Connell R G, Dockree P M, Robertson I H, Bellgrove M A, Foxe J J and Kelly S P 2009 *Journal of Neuroscience* **29** 8604–8611

[47] Luck S J, Woodman G F and Vogel E K 2000 *Trends in cognitive sciences* **4** 432–440

[48] Lijffijt M, Lane S D, Meier S L, Boutros N N, Burroughs S, Steinberg J L, Gerard Moeller F and Swann A C 2009 *Psychophysiology* **46** 1059–1068

[49] Lautenbacher S, Dittmar O, Baum C, Schneider R, Keogh E and Kunz M 2013 *Journal of pain research* **6** 437

[50] Huotilainen M, Cowley B and Ahonen L 2016 *arXiv preprint arXiv:1608.08353*

[51] Gruendler T O, Ullsperger M and Huster R J 2011 *PloS one* **6** e25591

[52] Giraudet L, St-Louis M E, Scannella S and Causse M 2015 *PLoS one* **10** e0118556

[53] Fu S, Greenwood P M and Parasuraman R 2005 *Human brain mapping* **25** 378–390

[54] Sur S, Sinha V *et al.* 2009 *Industrial psychiatry journal* **18** 70

[55] Hannay H J 1988 *Experimental techniques in human neuropsychology* (Oxford University Press, USA)

[56] Saavedra C and Bougrain L 2012 Processing stages of visual stimuli and event-related potentials *The NeuroComp/KEOpS'12 workshop*

[57] Van Overwalle F, Van den Eede S, Baetens K and Vandekerckhove M 2009 *Social cognitive and affective neuroscience* nsp003

[58] Ito T A and Urland G R 2005 *Cognitive, Affective, & Behavioral Neuroscience* **5** 21–36

[59] Sakai T, Yoshida R, Tamaki H, Ogitsu T, Takemura H, Mizoguchi H, Namatame M, Kusunoki F, Yamaguchi E, Inagaki S, Takeda Y, Sugimoto M and Egusa R 2015 Electrodermal activity based study on the relationship between visual attention and eye blink *2015 9th International Conference on Sensing Technology (ICST)* pp 596–599

[60] RAJ Y V Erp peaks (p50,n100,mmn) `https://biokamikazi.wordpress.com/2016/01/19/erp-peaks-p50n100mmn/` [Online; accessed 18-April-2017]

[61] Hopf J M, Vogel E, Woodman G, Heinze H J and Luck S J 2002 *Journal of Neurophysiology* **88**

2088–2095

[62] Hillyard S A, Hink R F, Schwent V L and Picton T W 1973 *Science* **182** 177–180

[63] Hillyard S A, Mangun G R, Woldorff M G and Luck S J 1995

[64] Sutton S, Braren M, Zubin J and John E 1965 *Science* **150** 1187–1188

[65] Donchin E, Ritter W, McCallum W C *et al.* 1978 *Event-related brain potentials in man* 349–411

[66] Picton T W 1992 *Journal of clinical neurophysiology* **9** 456–479

[67] Linden D E 2005 *The Neuroscientist* **11** 563–576

[68] Donnerer M and Steed A 2010 *Presence: Teleoperators and Virtual Environments* **19** 12–24

[69] Olson L 2007 How often and why do people's eyes blink? `http://archive.boston.com/news/science/articles/2007/05/14/ how often and why do peoples eyes blink/` [Online; accessed 19-April-2017]

[70] Coltheart V 2011 *Tutorials in visual cognition* (Routledge)

[71] Nakano T, Kato M, Morito Y, Itoi S and Kitazawa S 2013 *Proceedings of the National Academy of Sciences* **110** 702–706

[72] Irwin D E 2011 *Attention, Perception, & Psychophysics* **73** 1374–1384 ISSN 1943-393X URL `http://dx.doi.org/10.3758/s13414-011-0111-0`

[73] Geoff R M and CTO E 2010 P300 and Emotiv EPOC: Does Emotiv EPOC capture real EEG? `http://hiran6.blogspot.in/2010/12/p300-and-emotiv-epoc.html` [Online; accessed 19-April-2017]

[74] Polich J 2007 *Clinical neurophysiology* **118** 2128–2148

[75] Mangun G R and Hillyard S A 1991 *Journal of Experimental Psychology: Human perception and performance* **17** 1057

[76] Ciesielski K and French C 1989 *Biological psychology* **28** 227–238

[77] Mackworth N H 1948 *Quarterly Journal of Experimental Psychology* **1** 6–21

[78] Mueller S T 2011 Pebl's clock test `http://pebl.sf.net/battery.html` [Online; accessed 20-April-2017]

[79] Monk T H 1989 *Psychiatry research* **27** 89–99

[80] Center N A R Task load index (tlx) `https://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov /20000021488.pdf` [Online; accessed 29-May-2017]

[81] Khatun S, Mahajan R and Morshed B I 2016 *IEEE Journal of Translational Engineering in Health and Medicine* **4** 1–8

[82] NovÃ V, Perfilieva I, Dvorák A *et al.* 2016 *Insight into Fuzzy Modeling* 49–80

[83] Haider M, Spong P and Lindsley D B 1964 *Science* **145** 180–182

[84] Revolvy Visual n1 `https://www.revolvy.com/main/index.php?s=Visual+N1` online; accessed 17-November-2017